

Enhancing Activity Recognition by Fusing Inertial and Biometric Information

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Abstract – Activity recognition is an active research field nowadays, as it enables the development of highly adaptive applications, e.g. in the field of personal health. In this paper, a light high-level fusion algorithm to detect the activity that an individual is performing is presented. The algorithm relies on data gathered from accelerometers placed on different parts of the body, and on biometric sensors. Inertial sensors allow detecting activity by analyzing signal features such as amplitude or peaks. In addition, there is a relationship between the activity intensity and biometric response, which can be considered together with acceleration data to improve the accuracy of activity detection. The proposed algorithm is designed to work with minimum computational cost, being ready to run in a mobile device as part of a context-aware application. In order to enable different user scenarios, the algorithm offers best-effort activity estimation: its quality of estimation depends on the position and number of the available inertial sensors, and also on the presence of biometric information.

Keywords: activity recognition, inertial sensors, biometric sensors, high level data fusion, personal health applications, context-awareness.

1 Introduction

Movement/activity recognition is the basis for many applications related to personal health, sport training and health risk detection or treatment, among others [1]. To date, the available techniques for movement analysis mainly rely on the use of vision or sensor-based approaches. The former presents privacy controversies and are geographically limited (cameras are usually deployed to cover well-bounded spaces - home, workplace, playground, etc.) [2]. The latter usually requires the user to wear or carry a set of sensors [3], inertial and/or biometric devices; although still intrusive, the continuous miniaturization of sensing technologies, their integration in mobile devices and the advances in smart textiles sketch a short-term scenario in which wearing sensors may be smoothly accepted by the users, whenever the application is worth it.

Assuming this approach, this paper explores a fusion strategy to opportunistically merge data coming from both

inertial and biometric sensors to estimate user's movement (or his 'atomic activities': walking at different paces, running, climbing stairs, taking the lift, sitting, standing still, etc.). The fusion algorithm is conceived to finally run in a mobile device. In particular the algorithm is designed to be integrated into a context-aware application, the so-called 'Activity Monitor' [3], which goal is to deliver context-aware notifications to prevent sedentary behavior during all day long. The application relies on gathering reliable movement estimations, to be subsequently evaluated in different timeframes and together with other context data, in order to determine if the level of activity is healthy enough with respect to a set of clinically predefined thresholds.

Implementing the movement detection algorithms to work anytime and to be embeddable in resource-constrained devices present special challenges: computational lightness, real-time response and possibility to work with variable sensing inputs are some of the requirements that are among our design objectives. Ideally, the algorithm will need to perform well when a single external inertial accelerometer is ready, but also to take advantage of bio signals, such as heart or respiration rate, when available, to provide a better estimation.

This paper is organized as follows. First, in Section 2, some selected previous works combining inertial and biometric information for activity estimation are presented. Section 3 describes the operational scenario for the 'Activity Monitor', detailing the type of sensors that are considered. How inertial information from accelerometers placed on different parts of the body can be merged to recognize a set of atomic activities is addressed in Section 4, analyzing the differences in detection accuracy depending on the available devices. Afterwards, Section 5 explains the relationship between biometric data (such as heart and respiration rate) and activity, and how it can be used to improve movement estimation. In Section 6 the validation tests are described together with the results obtained by each type of sensors separately, as well as merged. Finally, Section 7 concludes the paper, explaining some future lines of work.

2 State of the art

How to use only inertial systems to infer activity states has been widely explored in the literature (see e.g. [5] or

[6] for a review). Following, some previous works that have addressed the combination of biometric (heart rate, respiration rate, electromyography, etc.) and acceleration signals to calculate physical activity are reviewed.

Munguia et al. [3] uses five triaxial wireless accelerometers and a wireless heart rate monitor to recognize different physical activities and intensities for some of them (walking, cycling and rowing). They propose to use mean distances between axes, variance, energy, FFT peaks and correlation coefficients to successfully discriminate the activities. With respect to heart rate, they state that detection thresholds are very dependent on the physical fitness level of each individual.

Yazaki and Matsunaga [7] propose to evaluate activity levels by using a chest-worn sensor measuring heart rate (processed to obtain the intensity of exercise with the zero to peak formula) and acceleration. Authors suggest that heart rate should not be taken into account when estimating activity in stressful situations, as the estimated intensity of exercise is modified due to emotional tension.

The particular needs of COPD patients are considered by Patel et al. [8], who uses accelerometers and gyroscopes to capture motion data, and heart and respiration rate to capture physiological responses to a range of activities of daily living and physical exercises. After comparing 6 different types of classifiers and analyzing the influence of the information on the different axes and the number of sensors available, authors conclude that high recognition accuracy can be achieved by using data independent from the individual and also by using a reduced sensor set, if the sensors are carefully selected.

Strath et al. [9] measures heart rate, oxygen consumption and uses accelerometers (wrist, hip and thigh) and a pedometer to estimate Energy Expenditure (EE) in different activities. They conclude that the pedometer and the hip accelerometer underestimate the EE by around 1 MET (Metabolic Equivalent of Task), while heart rate slightly overestimates it. With respect to motion sensors, they claim that they are not good stand-alone predictors of EE, as e.g. lower limb sensors do not account for upper limb activity, such as washing dishes. Authors state that individualized HR (heart rate)-VO₂ (oxygen uptake) regression equations provide greater accuracy as they account for individual levels of fitness and that the combination of heart rate and motion sensors provides better results.

Roy et al. [10] uses a combined surface electromyography (sEMG) and accelerometer (ACC) sensor system (placed on 8 different parts of the body) for monitoring activities of daily living in patients with stroke. To analyze the data a multilayered neural network and an adaptive neuro-fuzzy inference system were used. Their conclusions show that only 4 pairs of sensors are needed to get the highest accuracy. The algorithms use specific training for each individual and require multiple repetitions of each task to have sufficient data for training and test purposes.

Chan et al. [11] uses a multilayer fuzzy clustering algorithm fed with electrocardiogram and acceleration measurements to classify physical activity and a discrete wavelet transform to retrieve time-varying characteristics of heart rate variability during those activities. The results show that there are larger heart beat fluctuations while performing low intensity activities, such as standing or lying down.

In the reviewed literature, different views are shown regarding biometric information: some conclude that it is not useful, others propose a general formula while others state that an individual training is needed. Following it is analyzed to which extent and under which conditions biometric information (heart rate, oxygen consumption, skin temperature and respiration rate) may be integrated in personal real-time mobile applications.

Most of the mentioned works rely on numerous worn acceleration sensors to make the algorithms work. The feasibility of porting the proposed algorithms to mobile devices to perform activity detection in real time is not considered. Our proposal aims to work in these conditions, for different application scenarios (where not every inertial sensor may be available), and as a preliminary step to an activity recognition system capable of relying on mobile embedded inertial technologies.

3 Application scenario

This work proposes a lightweight algorithm to recognize activity, so it can be integrated in a mobile device to do detection in real time. In particular, the algorithm is to be integrated in the Activity Monitor, an application that aims at providing continuous feedback to the user on his level of daily physical activity, together with the evolution of health status (from bio sensors) when available.

As explained in [4], the Activity Monitor evaluates the user's sedentary lifestyle by calculating the 'energy cost' of each atomic activity performed and integrating it during a temporal window. The energy cost is measured in PARs (*Physical Activity Ratio*). The number of PARs associated to any activity only depends on the activity itself and not in the person performing it: PARs are multiple of BMR (*Basal Metabolic Rate*) per minute (BMR is the minimal rate of energy expenditure compatible with life). Mapping from 'activity' to its associated PAR is done consulting specific nutrition tables.

The application is designed to connect to the following Bluetooth hardware to be potentially worn by the user (depending on the individual's situation):

- Bioharness BT from Zephyr, which is a chest belt that provides heart rate, respiration rate, skin temperature and posture from a 3 axis accelerometer.
- The fingertip pulse oximeter Onyx II model 9560 from Nonin Medical, which can measure the pulse, as well as the oxygenation of the user's hemoglobin.
- A set of Shimmer wireless sensors by Intel, each of them with embedded 3 axis accelerometers. These

sensors are to be placed on the right foot and right part of the hip.

The Activity Monitor assumes that atomic activities can be inferred in real-time from data acquired from all or some of these sensors (bio and inertial). Following a best-effort criterion, the application should work properly when a single inertial is worn (at least one is required for operation), enhancing its performance if additional sensors are available. Additionally, the set of sensors on which activity is estimated could vary over time, in particular to take advantage of the non-intrusive inertial systems embedded in the mobile device itself.

The activities that have been initially considered for the Activity Monitor are: walking at different paces, running, standing still, sitting, lying down, climbing the stairs or taking the lift. As the final objective of the application is to detect recurrent sedentary behavior during all day long, these activities are a starting point to estimate the consumed energy when accomplishing normal indoor life – e.g. working (outdoors evaluation is done relying on GPS trajectories). The number of activities considered is to be increased to better adapt to other situations (e.g. commuting from home to work, practicing sports or doing housework).

Next the strategy to lightly compute activity relying on inertial sensors, to subsequently study how to integrate bio information, is described.

4 Light activity recognition using inertial sensors

In order to detect activities using inertial sensors, a light algorithm relying on step counting, velocity estimation and movement feature analysis is proposed. The algorithm works on acceleration data from hip, foot and chest inertial sensors, needing at least one of them to be enabled.

The algorithm works as follows, so as to be easily embedded in a mobile device fulfilling the objective of not requiring high computational capabilities. The signals are first analyzed by a counting step algorithm to detect if walking (at different paces) or standing activities are being carried out. In parallel to this, several features of these signals are studied using amplitude and time thresholds, and a final decision of the activity that is being performed is taken comparing the different results thrown by these analyses. Two datasets have been considered: the first one is used for feature selection and training and is composed of individual activities performed by 13 different people. The second one, described in Section 6, has been used for validation.

Table 1 shows the list of the parameters of the different signals that are processed in the algorithms to make the decision of the activity that is being carried out at a specific moment. These parameters are decided after an analysis of the signals gathered from different users performing individual activities. In the table, it is also included the features that make feasible that an activity can be distinguished from the others.

Table 1 Relationship between the activities and parameters considered for discrimination

Parameter	Activity	Features
Peak amplitude (foot sensor)	Walking slow	Intensity
Peak frequency (foot sensor)	Walking	
Posture (chest sensor)	Running	
Heart rate		
Respiration rate		
Skin temperature		
Vertical minimum analysis (chest sensor)	Stairs	
Distance-between-axes analysis (foot and hip sensors)	Sitting	Posture
	Lying down	
Variance	Standing	No movement
Vertical minimum analysis (hip sensor)	Lift	

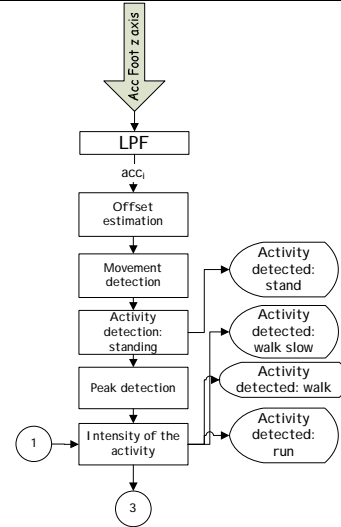


Figure 1 Step counting algorithm using foot accelerometer. Numbers in circles connect the diagram to the same symbols in Figure 2 and Figure 4. That is, e.g. that posture information (1) is used to decide walking pace.

Figure 1 and Figure 2 gather the main processing and analysis phases of the algorithm, as well as the parameters of the signals that are finally considered. Figure 1 shows how the step counter algorithm works, while Figure 2 shows the processing strategy when accelerometers placed on the foot, hip and chest are available. It is important to

note that data fusion requires temporal alignment of the signals so as the algorithm can correctly interpret changes in the values of the features as possible changes in the activity.

The steps that the user walks and their frequency are first computed from the z-axis acceleration signal measured on the right foot. This signal is low pass filtered in order to eliminate high frequency noise. This filter introduces a 1 second delay. The algorithm considers that the user is standing still as the system is switched on, so the offset of the measurements can be estimated and subtracted from the following samples.

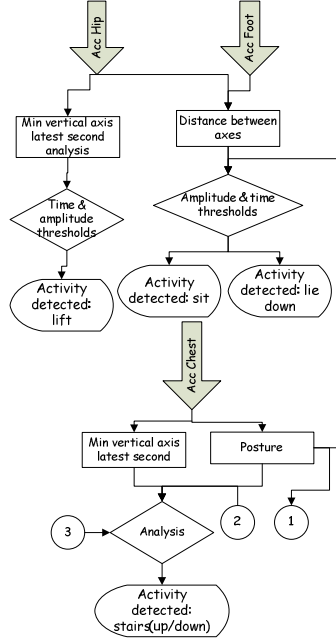


Figure 2 Hip, foot and chest accelerometer information fusion. Numbers in circles connect the diagram to the same symbols in Figure 1 and Figure 4.

The *Standing* activity is recognized when the variance of the latest 6 samples is below a threshold for 1 second. In other case, the algorithm aims at detecting minima and their corresponding peaks. To prevent false detections, a threshold is compared to the maximum value of the peak and the amplitude of the detected peak is required to be above the amplitude of the latest peak detected multiplied by a factor. This amplitude is computed as:

$$A = A_{peak} - A_{min} \quad (1)$$

To decide the intensity of the activity the frequency of the two latest peaks is considered, being:

$$f = f_s / \Delta i \quad (2)$$

Where Δi is the number of samples between the peaks and f_s is the frequency at which the samples are measured. It is important to notice that between two detected peaks, two steps are walked (the sensor is placed in a single foot). The velocity is then computed as:

$$y = B * f / (1 - C * f) \quad (3)$$

The model with parameters $B = 0,53$, $C = 0,17$ is the result of fitting equation (3) to experimental data obtained from the results of 13 people (6 men, 5 women and 2 children included) who were requested to walk slow, walk, walk fast and run for a specific distance. The results show a linear relationship between the step length and the frequency of steps, so the velocity can be fitted to the frequency of the steps as it is shown in Figure 3.

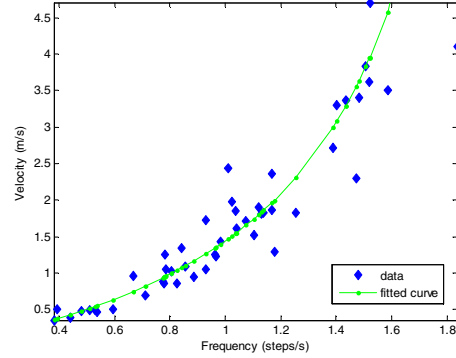


Figure 3 Moving velocity related to step frequency, and fitted curve.

To differentiate among the activities *Walking Slow*, *Walking* and *Running*, the following thresholds, estimated from the measurements used to get the velocity - frequency curve, are considered:

$$\begin{cases} v(m/s) \leq 0,9 & f < 0,75 \rightarrow \text{walk slow} \\ 0,9 < v(m/s) < 2 \rightarrow \text{walk} \\ 2 \leq v(m/s) & f > 1,3 \rightarrow \text{run} \end{cases} \quad (4)$$

Additionally, the sensor placed on the chest gives information about the posture (degrees of inclination from the vertical) every second. In this way, the posture relative to the one adopted during the initial standing period that calibrates the system is computed. Then, thresholds are used to detect when the inclination has increased and decide whether the user is climbing stairs or running by fusing these results with the ones provided by the step counting algorithm. In this way, false *Running* detections are corrected if the posture does not exceed the threshold at the same time, and *Climbing Stairs* is decided when the posture exceeds the threshold and the step counting algorithm has decided *Walking slow* or *Walking*.

Using the *Lift* (going up or down) is recognized thanks to the analysis of the peaks of the minimum values in the latest second that appear in the vertical axis of the hip sensor, that are detected using amplitude thresholds. The first peak has a short duration and is followed by a phase of inactivity, and the second one is followed by the movement of walking out of the lift, varying the time between peaks with the number of floors and the velocity of the lift. In this case, the building has 4 floors, so the user is expected to stay in the lift for less than a minute in the longest case, which is taken into consideration in the time threshold used to determine the activity.

The sensor placed on the hip plays an important role when distinguishing between *Sitting* and *Lying down*. The main difference between these two activities is that the

signal gathered from the foot sensor does not vary when sitting but it suffers a big change when lying down. Nevertheless, the hip signal varies in both cases. In this way the differences between the x and z axes for the foot and hip sensor values in the latest second are analyzed using amplitude thresholds corresponding to these two activities to decide between them. It is also considered that you must be sitting or lying at least for half a minute to detect the activity.

Going down Stairs is a challenging activity to be distinguished from the others, since the signal gathered from the foot is quite similar to the one received when walking. The minimum values of the latest second of the chest vertical axis are compared with a threshold and this activity is decided when *Climbing Stairs* has not been detected and the step counting algorithm has decided *Walking* or *Slow Walking*.

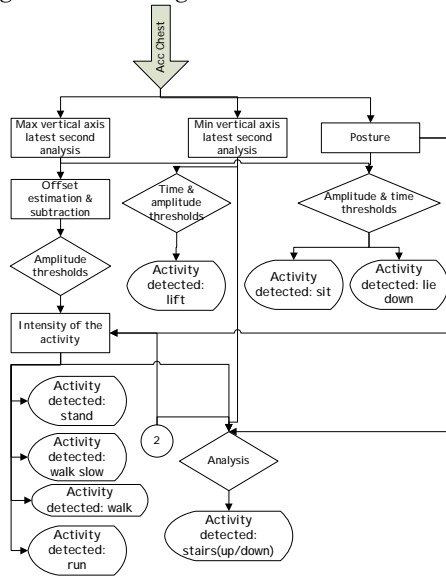


Figure 4 Activity recognition using the chest accelerometer. Numbers in circles connect the diagram to the same symbols in Figure 1 and Figure 2.

Figure 4 shows how the activity recognition is carried out when the chest accelerometer is the only device that is available. In this way, some modifications have been introduced. The step counting algorithm is not used anymore and thresholds are applied over the maximum value of the latest second of the signal measured in the vertical axis instead. The rest of the algorithm is the same, replacing the signals by the corresponding ones from the chest accelerometer when needed.

5 Activity recognition using biometric sensors

As explained in Section 3, the ‘Activity Monitor’ gathers bio information from the Zephyr chest strap, so information about heart and respiration rates, as well as skin temperature are available. In addition, the oxygen saturation is provided by the Onyx sensor. Our objective

is to correlate all these bio parameters with movement, in order to analyze to which extent is feasible to use them for activity recognition.

From our validation dataset it has been verified that the heart and respiration rates increase with the intensity of the activity that is being performed. As the biometric constants during resting state change from person to person, not only as it logically happens in different age ranges, but also among people of the same age, the relative variations of the parameters have been considered.

In the signals gathered, it is shown that these parameters (heart and respiration rates) can only be used to recognize changes from light to intense activities, such as running and going up or down stairs (and vice versa). For instance, Figure 5 shows the changes produced in the heart rate while performing the activities: walking, running, going up/down stairs, etc. This means that biometric information by itself can only show a level of intensity of the activity, which combined with a parallel detection of the activity, obtained for instance with inertial sensors, can reduce the mistakes of the recognition. The bio response to the performance of different activities strongly depends on the physical characteristics of the individual. For instance, if the individual practices sport regularly, the respiration rate will adapt at the same time as the intensity of the activity increases, but if he leads a sedentary life style the respiration rate increases at the end of the activity to get breath back.

Finally, these signals do not change at the same time as activities, since it takes some time for the physical response to adapt to movement transitions, so the analysis of this information introduces always a delay in the detection.

It has also been noticed that skin temperature decreases up to a couple of degrees for some users while they are performing an intense activity such as running or going up stairs but it only changes slightly for other users. The same phenomenon occurs with the oxygen saturation.

Summing up, it can be stated that knowing the specific characteristics of the user is essential to be able to establish the appropriate thresholds to detect changes of activity intensity and merge biometric information with inertial information.

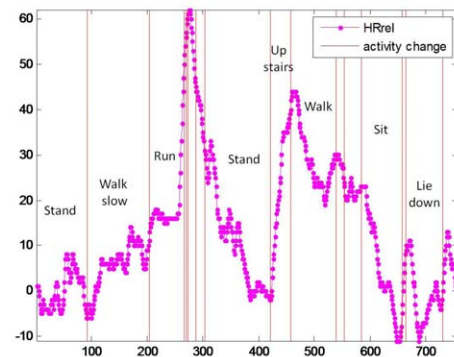


Figure 5 Changes in heart (beats per minute) rate during several activities.

Finally, Figure 6 shows how to use in the algorithm the information provided by the biometric sensors together with the inertial sensors.

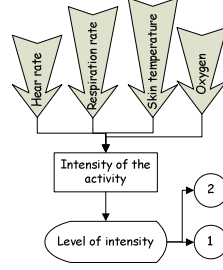


Figure 6 Scheme of biometric sensor information fusion.

6 Experiments and results

6.1 Description of the experiments

Our system has been validated on a dataset which gathers information from the whole sensing system (bio chest belt, accelerometers and oxymeter) for five male walkers, who have been asked to cover the following sequence of activities (shown also in Table 2):

- Walk slowly along a corridor
- Run in the same floor along three corridors
- Wait for the lift
- Walk into the lift
- Take the lift to go to a lower floor
- Walk out of the lift to a notice board
- Stand in front of a notice board.
- Go up the stairs two floors.
- Walk along two corridors.
- Go down the stairs one floor.
- Walk into an office
- Sit
- Walk to another office
- Lie down
- Get up and stand

The duration of each activity has not previously established, so it depends on the walker idiosyncrasy. In Table 2 is included their rough durations.

In Section 6.2 there is an analysis of the results achieved when detecting activity for these five individuals using inertial sensors separately; some conclusions on the accuracy that can be reached with inertial and biometric information fusion are shown next.

In order to interpret data, it is important to bear in mind that signals from the Shimmer motes have been gathered at 50Hz frequency and information processed from the Bioharness BT sensor is provided at 1 Hz frequency. This means that a time variable is established in the algorithm to process the information aligned at the appropriate instant.

Results have been computed using Matlab. The algorithm is fed with the signals of the whole sequence of activities (real time processing implies some changes on this strategy). In order to minimize false positives, the activity identification is not immediate, but provided after a subsequent repetition of the detection of a given activity.

For instance, ‘standing’ is delivered after the activity is detected during one second. When considering the ‘lift’ activity, it has to be taken into account that it cannot be detected until finished, since it is necessary to know the frequency for the on-floor-stop signal’s peaks (those that are detected when the lift stops in each floor). In consequence, some time delay in the recognition has to be assumed for real time operation. Nevertheless, most of applications relying on real-time activity may assume a given delay, and use additional data to improve previous estimates e.g. to guarantee the quality of historical records or the evaluation in the medium term. In the results shown in Table 2 these delays are not considered.

In our detection system, some activities (*Walking*, *Walking slow* and *Running*) are not updated until two consecutive detections are gathered. This strategy prevents the system from continuously switching between activities in case the information available is not enough to clearly distinguish one from another. The delay depends then on the step frequency, and there is also a one second delay in the step counting algorithm (introduced by the initial filtering). To update the activity to *Standing*, a delay of one second is introduced in the system. Activities detected using the information provided by the Zephyr have also a delay, since the frequency of that information is 1Hz.

6.2 Detection with inertial sensors



















Table 2 shows the results achieved when the foot, hip, and chest sensors are available (column (a)), and when the user is only carrying the chest sensor (column (b)).

When the duration of the activity is ‘long’ (>30 secs), the proposed algorithms achieve good accuracies. Detection percentage deteriorates when identifying ‘transitional’ activities, those carried out for a short period of time between two activities with ‘long’ duration (e.g. as waiting for the lift and walking to get into the lift). When activities are performed during ‘short’ time, detection varies depending on the available accelerometer.

It can be noticed that one of the most challenging activities to be detected is the slow walk period, since it is usually confused with normal walking, in part due to the fact that, for our experiments, pacing speed is subjective (dependent on the walker).

If the results achieved in both columns are compared, the percentage of global detection has been reduced by almost a 10% when relying only on the chest sensor. The probabilities of detection of *Standing* and *Walking slow* activities are reduced, due to the fact that now there is no counting step algorithm to estimate the velocity of the movement but thresholds applied to the accelerometer signal, which usually throw less accurate results for these activities.

Table 2 Activity detection results (%). (a) Using foot, hip and chest accelerometer. (b) Using chest accelerometer

	Activity		Duration (s)	% detection (a)	% detection (b)
					
Route of activities 		Stand	70	99,9	95,5
		Walk slow	125	84,7	45,8
		Run	60	93,4	94,8
		Stand	7	45,1	0
		Walk	5	40,6	8,4
		Lift	13	100	98,2
		Walk	13	85,5	90,9
		Stand	120	99,3	71,5
		Up stairs	40	85,6	92,8
		Walk	80	89,8	92,4
		Down stairs	15	65,2	67,6
		Walk	30	98,2	97,4
		Sit	60	95,5	99,2
		Walk	8	44,8	62,7
		Lie down	60	94,0	99,4
		Stand	60	93,0	93,8
Global walk				78,5	72,3
Global Stand				84,3	65,2
Global				89,4	81,3

6.3 Including biometric information to enhance activity recognition

As it has already been mentioned in the previous section, biometric information is highly related to the characteristics of the individual. Thus, it has not been defined a walker-independent general rule to derivate activity estimation from biometric data.

The signals gathered in our experiments show that a training period for each walker is needed to define customized strategies that can help to improve inertial-based activity detection with data from biometric sensors. For example, following there are some cases for which

activity detection improves by fusing data from inertial systems with:

a) *Skin temperature or oxygen variations*: The *Running* detection in the case of a user was around 72 %; due to the fact that, for this individual, the skin temperature decreases during intense activity about 2 degrees, it has been possible to establish some thresholds to integrate this information. The detection percentage has increased to around 91%. Oxygen variations are similar, and can also be used for this purpose.

b) *Heart rate*: when detecting *Slow Walk* by only using the chest accelerometer, some thresholds have been applied to the heart rate signal to correct the false detections during that activity. In this case the percentage of detection has increased between 3 and 4.5 % depending on the user. This approach has also improved the results of transitional walking activity (between *Sitting* and *Lying down* activities) by an 8%.

From these experiments, it is possible to state that designing a machine learning method, capable of adapting its performance depending on the walker after a training period, can be useful to enhance the activity detection results using biometric information.

When working with real time applications, it is important to note that biometric information is not temporally aligned with the information provided by the inertial sensors, because these parameters do not change instantly with the activity. Thus, biometric data may improve activity detection if the movement continues for a while but, in general, these data are not reliable for instant movement detection.

7 Conclusion

This work presents a high-level data fusion light algorithm to estimate movement and activity from a variable number of inertial sensors placed on the feet, at the hip and at the chest. The algorithm is ready to offer the best estimate depending on the available sensors. For continuous activities (lasting above 30 secs), the proposed algorithm performs around 90%. This detection rate is good, regarding the simplicity of the algorithm to make it embeddable in a mobile device.

The step-counting and velocity-estimation algorithm has been effectively integrated in a mobile application called Activity Monitor, demonstrating to be light enough to cohabit with the rest of processes and sensors. The Activity Monitor still relies on external inertial devices for activity detection, but future works will necessary address the integration of the inertial technology available in the mobile device. Strategies to elucidate the position of the mobile device with respect to the user's body will be needed, in order to apply the correct activity estimation algorithms depending on the mobile position.

In order to improve activity estimations, the paper has also explored how to combine acceleration-based estimates with biometric information. From the experiments, it is possible to conclude that biometric information can be used to improve the performance of

acceleration-based techniques, but to do it in an efficient way it is necessary to know about the specific characteristics of the user (e.g. life style and health status). The signals measured show that, for instance, oxygen and skin temperature variations are intrinsic to each user; depending on the individual, these parameters may come to be useless to significantly improve the detection in some cases, while very helpful in other occasions. Heart and respiration rates vary differently depending on the habits of the user, mainly due to the sedentary or sportive life that he leads.

An important issue when fusing information from biometric sensors is time alignment. On one hand, sampling frequencies are different from one sensor to another; on the other hand, changes in biometric signals do not happen at the same time as the user begins to carry out an activity, but usually later. For real time applications, this delay has to be properly handled, although it is feasible to plan a postprocessing correction strategy, which may improve estimations for historical records.

A challenge for further work relies on the design of a strategy to personalize the processing of biometric information to each individual's features. This strategy could be based on machine learning techniques, ready to calibrate biometric algorithms before merging their output with inertial-based estimates. The learning technique should be trained to analyze the variations of bio signals during different annotated activities for a sufficiently long time; additionally, the individual could be requested to provide the system with initial information about habits in order to facilitate the process. The algorithm should be dynamically adaptable and updatable, ideally capable of working on external situations that may influence these bio parameters, for instance, laughter or stress.

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